CONTROL OF NONLINEAR, ADAPTIVE SYSTEMS

by

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A thesis submitted to the faculty of
The University of Utah
in partial fulfillment of the requirements for the degree of

Master of Science

Department of Psychology

The University of Utah

December 2007

THE UNIVERSITY OF UTAH GRADUATE SCHOOL

SUPERVISORY COMMITTEE APPROVAL

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ABSTRACT

Differences in property characteristics of natural and engineered systems, such as transparency, linearity, and adaptability, are likely to result in differences in human ability to control these systems. This study explored human performance on a simulated control task in which system characteristics of adaptability and linearity were manipulated. An experiment was conducted in which 53 participants used a joystick to perform a manual control task. A secondary stimulus response task was used to compare cognitive demand between the conditions. The results indicate that control performance was worse and cognitive demand was greater in the control tasks that simulated the natural system characteristics of adaptability and nonlinearity. Potential applications of this research include furthering experimental exploration of control differences between natural and engineered systems as well as motivating the development of a control theory specific to human interactions with natural systems.

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INTRODUCTION

Every day, millions of people monitor and control system behavior. Drivers control the movement of their automobiles, health care professionals track the status of their patients, and meteorologists track weather systems. Some systems, like the automobile, are engineered; other systems, like human patients and weather systems, occur naturally. There are important differences in how engineered and natural systems are formed; there are also differences in how they operate. These differences likely influence the system behavior and the manner in which system behavior changes over time. These differences may also affect people's ability to control system behavior and keep control error at a minimum. The purpose of this research is to explore human ability to cope with different types of system behavior within natural and engineered systems.

Control refers to an individual's ability to manipulate a system's progress or behavior. There are a variety of circumstances when controlling a system is necessary. A pilot manipulates the aircraft control yoke and pedals to keep the aircraft in a safe flight path amid changing environmental conditions (Edwards, 1990). Advanced warnings for weather systems, such as tracking hurricanes, help emergency response personnel make evacuations that save lives (Kang, Lindell, & Prater, in press). In health care, anesthesiologists monitor vital signs while administering drugs that temporarily inhibit consciousness, memory, and sensation (White, 1987). In each of these examples, it is important for the operator to not only understand the past and current states of the system, but also to be able to predict its future states. What happens to control performance when the behavior of a system changes from its normal state of operation or behaves in an unanticipated way? Airplanes encounter turbulence, high pressure areas collide with hurricanes, and patients' vital signs change during surgery. Unanticipated changes to system behavior could prevent the operator from accurately predicting the future system state which may lead to an increase in control error. Control and prediction errors in some systems can be catastrophic. In 2004 it was estimated that weather-related complications caused 111 airplane crashes (Jarboe, 2005); in 2005, hurricanes Katrina and Rita caused more than $108 billion in damages and over 1,400 deaths (Ross & Lott, 2006). It is estimated that human error in health care is responsible for 98,000 deaths annually (Kohn, Corrigan, & Donaldson, 2003). Keeping such costly errors at a minimum should be a primary goal when dealing with system control.

Control error can be operationalized as the distance between the current state of the system and the system's goal state (Jagacinski & Flach, 2003). For example, when driving, error can be measured as the distance a driver deviates from the lane in which he should be traveling. Being able to track and predict the actual path of a hurricane has important financial and safety implications, not only for those living in its path, but also for those who would be needlessly evacuated due to tracking error. In health care, control error can arise when patients have adverse reactions to drugs or do not receive an appropriate dose. Control errors such as these often lead to tragedy.

An important component of control is the ability to follow the current state of a system. Tracking refers to an observer's ability to follow a system's progress or behavior. Two methods commonly used to measure tracking performance are attentive tracking and manual tracking. Attentive tracking involves using attention to monitor targets, particularly when there are multiple targets that cannot all be followed with eye movements. Manual tracking involves using a device, such as a joystick or mouse, that controls a cursor to follow a target (Allen, McGeorge, Pearson, & Milne, 2004; Miyake, Loslever, & Hancock, 2001; vanMarle & Scholl, 2003).

A great deal of research has looked at human proficiency in system control to find methods to reduce error. Previous studies involving tracking tasks have examined cognitive abilities such as attention, dual-task performance, and mental workload (Haga, Shinoda, & Kokubun, 2002; Strayer & Johnston, 2001). Functional magnetic resonance imaging (fMRI) has been used to investigate cortical regions that are active during attentive tracking (Culham, Brandt, Cavanagh, Kanwisher, Dale, & Tootle, 1998). Researchers have also explored the influence of a myriad of variables on a human operator's tracking performance including: movement frequency (Jagacinski, Liao, & Fayyad, 1995; Noble, Fitts, & Warren, 1955; Stark, Iida, & Willis, 1961), type of visual display and control dynamics (Liao & Jagacinski, 2000), one- vs. two-dimensional target movement (Watson & Jones, 1998; Watson, Jones, & Sharman, 1997; Ziegler, 1968), gender (Joseph & Willingham, 2000; Thomas & French, 1987; Wright & Pane, 1985), perceptual motor experience (Joseph & Willingham, 2000; Kuhlman & Payne, 1991), multiple targets (Allen et al., 2004; Pylyshyn & Storm, 1988), tracking objects vs. substance (vanMarle & Scholl, 2003), precision of informational feedback (Hunt, 1961; 1964), and G forces (Repperger, Rogers, Frazier, & Van Patten, 1982). This vast body of research has examined human tracking performance from numerous angles; however, there remains a lack of research exploring the influence of output pattern change on tracking error. Because many real world systems exhibit output patterns that are adaptive and thus susceptible to change, there is clear utility in studying people's ability to track these systems.

One potential limitation of tracking research to date has been the tendency to incorporate mainly pseudorandom outputs for the tracking targets instead of learnable repeating output patterns. Random target outputs are typically used to prevent the operator from being able to predict the future location of the target. However, in most real word tracking tasks (e.g., driving, healthcare, weather prediction) the target output is not random.

Despite their general predictability, output patterns in real world tracking tasks are susceptible to alteration. Transitional moments, when predictable output patterns change and adapt in response to outside forces, may be a critical time for tracking and control performance. An unanticipated change to a learned output pattern would likely result in a decline in tracking performance. The degree to which performance declines may depend on the nature of the change to the output pattern. The current research aims at identifying how certain system characteristics (i.e., transparency, adaptability, and linearity) can influence human tracking and control performance. Once we understand the effects of these characteristics, we may be able to better understand some human limits for controlling systems. In addition, we may also discover concepts to aid in the improvement of human control interfaces for real world applications.

Literature Review: System Types

Systems Decomposed

A system can be defined as an organization of collective components. A system is not a physical entity that exists in the world independent of the observer; rather, a system is a scientific construct used to help us understand the world (Jagacinski & Flach, 2003). System boundaries are assigned artificially by an observer. Everything outside the subjectively constructed limits of the system is labeled as the environment or ecology. However, systems do not necessarily exist independent from their ecology; components within a system interact with elements from the environment. A system receives stimuli and information from the environment; these are termed inputs. The environment in turn receives information and feedback from the system, or outputs. For example a car, independent from its environment, can be classified as merely an organized collection of metal alloys, plastics, fabric, and rubber. With the addition of fuel, air, and an electrical spark, the engine provides a physical translation of energy to create locomotion. Without an environment in which to travel, however, an automobile has no transportation utility. Furthermore, the automobile by itself could be classified as a system or a collection of systems. Is the fuel system separate from the engine; if it is separate, is the pump that draws the fuel from the gas tank to the engine merely a component of the fuel system or is it a system unto itself? Clearly, the boundaries of a system depend upon the subjective point of view of the observer.

The complexity of a system affects our ability to identify and adapt to changes within that system. Complexity is "that which is made up of many elaborately interrelated or interconnected parts" (Webster's New World Dictionary, 1984). It is not enough to understand the individual system components and their functions. We must also understand how the individual components interact together to influence the behavior of the whole system. According to information and computation theories, complexity is the amount of independent information necessary to describe all of the components and interactions within a system (Bar-Yam, 1997; Collier & Hooker, 1999). The longer the description required to give adequate details of a system is, the more complex the system is. For example, the rules to the game of chess can be delineated in a few pages, including a description of the system space (chess board), system components (chess pieces), and component relationships (valid moves). By contrast, defining a national government requires thousands upon thousands of pages to explain the system space (nation), system components (public and private sectors), and component relationships (laws and policy). Compared to national government, chess is relatively low in complexity; it has fewer interconnected parts, is easier to understand, and requires less information to describe the system. Hence, systems exist on a continuum of varying levels of complexity.

Engineered systems (machines) often have a high degree of redundancy, relatively few interconnected parts, and moderate physical organization, resulting in a low level of complexity (Collier & Hooker, 1999). Conversely, natural systems (e.g. living systems, weather systems) have been identified as highly complex because they require a large amount of information to describe their elaborately interconnected components and how these parts interact with one another (Bar-Yam, 1997; Rind, 1999; Whitesides & Ismagilov, 1999). Complex systems cannot be explained by a simple description of their composite parts; they require a complete description of every part and every possible interaction between these parts. When separated from one another, system components may not continue to display the same properties and characteristics that they display collectively. If any of the components or their interactions change, then the properties of the whole system can also change. Such changes to complex systems presumably influence the behavior (output) of the system and could affect an operator's ability to track the system.

Previous Research. A great deal of research has been done on human control of complex, dynamic systems (Brehmer, 1992; Brehmer & Dorner, 1993; Dorner, 1996 ; Green, 2001; Gonzalez, Thomas, & Vanyukov, 2005; Kantowitz, 2001). Experts in this area have concluded that humans have difficulty understanding and controlling complex dynamic systems due to an inability to comprehend all of the influences of their actions (Dorner, 1996; Cellier, Eyrolle, & Marine, 1997; Kleinmuntz & Thomas, 1987; Paich & Sterman, 1993; Sterman, 1989; Smith, Suchanek, & Williams, 1988). Because people may not understand the long term effects of their actions, they may make decisions that actually increase error, instead of decreasing it. When people attempt to control complex systems, they tend not to pay attention to the history of the system, or previous inputs. People do not consider indirect (nonlinear) component interactions and their consequences; they are also not typically aware of the potential for multiple consequences of a single action. When changes occur in the system that result in changes to the system's output, operators often fail to compensate for them with appropriate input manipulation. This is dangerous because often critical resources, including our lives, literally depend upon our own and others' abilities to track complex systems.

System Types: Natural vs. Engineered Systems

In addition to differences in complexity, systems vary on other dimensions. Systems can be classified as those that occur naturally and those that are created by humans. Examples of natural systems include living organisms and weather systems. Systems created by humans, or engineered systems, include aircraft, power plants, computers, and other machinery.

Natural and engineered systems share two important characteristics; their defining properties and their functional capabilities are causal (Collier & Hooker, 1999; Flach, 1999). These characteristics indicate that the internal component relationships are deterministic and that there is a potentially predictable relationship between the internal components of any system. Predictability is especially useful when tracking systems because it allows an operator to anticipate the system's future state, resulting in less tracking error. Causal relationships between engineered components can be clearly delineated and evaluated. For example, within the cylinder of an internal combustion gasoline engine, fuel and air are compressed by the piston. The conditions are then ideal for igniting the volatile mixture. An electrical spark from the spark plug causes a small explosion and forces the piston back down the cylinder. Likewise, causal relationships can be evaluated in natural systems. Within the chloroplast cells of plant leaves, chlorophyll reacts with photons from the light to change carbon dioxide into carbohydrates, which are used to form various organic compounds used by the plant. It is apparent in both examples that the presence of one component causes the other components to interact.

Even though natural and engineered systems both have causal defining properties and causally grounded functional capabilities, there are fundamental differences between them in terms of adaptability, linearity, and transparency. These differences may influence our ability to understand the internal relationships within both natural and engineered systems. These differences may also affect how the defining properties and functional relationships of system components can change.

Adaptability. Natural systems can be identified as organizations of existential elements that occur without intentional design or manufacturing. Instead, they come to exist in their current state through a process of re-organization and evolution (Bar-Yam, 1997; Raichman, Gabay, Katsir, Shapira, & Ben-Jacob, 2004; Tompkins & Azadivar, 1995). They do not spontaneously change their defining parameters; rather, they adapt as old states become unstable (Kelso, Ding, & Schoner, 1992). The bristlecone pine, for example, is a tree that thrives in harsh, high altitude conditions in the western United States where other trees cannot live. By keeping only a small portion of the wood alive at one time, these trees can live for more than 4,000 years at altitudes of 11,000 feet. The bristlecone survives in conditions where other trees fail because its internal component interactions have successfully adapted to the changes in its environment. As a result of the codependent existence with their environment, natural systems are sensitive to and vulnerable to changes in their environment (Collier & Hooker, 1999). This sensitivity gives natural systems the capacity to adapt and meet the changing demands placed upon them by their environment (Arthur, 1999; Raichman et al., 2004). Seemingly, the composition and behavior of natural systems results from extensive adaptation to the environment and through evolution.

In contrast to natural systems, engineered systems are created through a process of intentional design and manufacturing to provide solutions to specific, practical problems and to suitably perform a known number of specific tasks. Blueprints are used to establish the highest levels of precision with the fewest complications, and with little to no room for randomness, errors, or wastefulness (Raichman et al., 2004). Designers evaluate engineered systems using mathematical models and test them on their ability to solve a prescribed problem. People create prototypes and simulations to test the effectiveness and safety of these systems. The formation and adaptation of engineered systems is usually intentional and deliberate, a contrast to the vulnerable response to disruption which drives the formation of adaptive natural systems.

Engineered systems are generally neither autonomous, nor anticipative, and are typically not adaptive. There is current research with engineered systems that uses genetic algorithms in an attempt to adapt these systems to their environment (Cayzer & Aickelin, 2002; Goldberg, 1989; Moradi-Jalal, Rodin, & Mariño, 2004). However, genetic algorithms are typically used only to produce optimal solutions that are then incorporated into the design of the system rather than enabling engineered systems to adapt to changes. Other engineered systems, such as those with feedback loops, may have the capacity to self-regulate but only within a predetermined set of parameters. Currently, engineered systems do not adapt to changes in the environment without the aid of a human operator, whereas natural systems are often able to adapt to environmental changes on their own.

Linearity. Along with the variance in their adaptability, engineered and natural systems also differ in terms of their linearity. Linearity is a mathematical property of a model. It describes the output of a system in relation to the input. If a system input X1 leads to an output Y1, and different input X2 leads to a different output Y2, and a third input, being the weighted sum of inputs X1 and X2, leads to a weighted sum output of Y1 and Y2, then the system is linear (Jagacinski & Flach, 2003). In short, linear systems are additive. It is possible to predict a linear system's output based on a simple summation of the inputs. Because a linear system's output can be predicted from its input, analysis of linear systems can be performed using a tidy reductionism approach (Reilly, 2000). Engineered systems are created to be linear because it is possible to solve linear problems analytically (Linsay, 1998).

Nonlinear systems are typically not additive. They do not always operate in a predictable manner. A small input to the system may cause an unpredictably large output and a large input may cause a small output. Nonlinearity that appears in engineered systems is often due to a malfunction, such as gear chatter or poor lubrication (Linsay, 1998). Because natural systems evolve and are not restricted to the limitations of design, they often display nonlinear behavior.

Transparency. Additionally, engineered and natural systems differ in terms of transparency. Transparency refers to an observer's ability to observe and understand the algorithms that govern a system's operation. In a transparent system, component relationships and interactions are visible and can be known. Nontransparent systems are those in which relationships are unknown. Natural systems are not transparent because algorithms describing component interactions and state variables have to be deduced and are generally not fully understood (Kelso, Ding, & Schoner, 1992; Sterman, 1994). Instead, models are developed in an attempt to mimic and describe their behavior. Although a model may closely approximate a natural system, it is merely an explanation of the system and is not perfectly identical to the system's actual behavior. In contrast, engineered systems are often designed for transparency (at least for the designer), due to the fact that component relationships are planned and calculated during the design. However, despite their transparency, complex engineered systems sometimes have unpredicted and unanticipated emergent behavior resulting from a lack of understanding of the causal relationships between system components (Weng, Bhalla & Iyengar, 1999). The transparency of a system can also influence our ability to cope with changes to its output. Specifically, people may be more able to correctly predict how change will affect output in transparent systems than in nontransparent systems.

Predictability. Compared to natural systems, engineered systems are generally easier to understand and maintain. A bicycle, for example, is a fairly simple engineered system. It has only a handful of interacting components. Consequently humans are able to keep them operational, or at least determine what is wrong when there is a problem, with relatively low effort. We can understand how the bicycle works and predict how it is going to work when problems arise. Conversely, highly complex systems, such as the space shuttle, pose various problems and challenges in maintenance and regulation. Higher complexity puts higher demands on the operator to gather information, integrate findings, and plan effective actions (Dorner, 1996). With over 2 million integrated components, the space shuttle is one of the most complex engineered system built to date. As the space shuttle is the most complex engineered system that we've managed to create, it proves to be the most difficult to control. Highly specialized teams, comprised of over 350 individuals, labor a whole year, a total of 728,000 man hours, just to perform the routine maintenance. Though difficult, time consuming, and often challenging, it is possible to maintain, control, and predict even the most complex engineered systems.

In contrast, natural systems may be more difficult to understand and predict. This could be due, in part, to the adaptive and nonlinear manner in which natural systems respond to system perturbation. Even natural systems that are simple in their structure, such as the bird flu virus, display behavior that is impossible to predict. We cannot foresee the effects that the virus will have on the world, despite the fact that it is relatively low in complexity. Hurricanes are examples of highly complex natural systems. Although accurate hurricane tracking and path prediction have improved drastically over the past 20 years, they still remain very difficult to track (Lindell & Prater, 2005). We are not able to predict exactly where a hurricane is going, or the level of the hurricane's intensity. The error in our predictions can lead to devastating consequences, as was dramatically demonstrated by hurricanes Rita and Katrina in 2005. Noticeably, there are important differences between characteristics of engineered and natural systems that likely result in variations in how these systems interact with the environment. An exploration of such variations follows, with a discussion of system stability, operation, and alteration.

Models of human performance in control settings typically propose a schema for how an operator plans and selects a sequence of actions to keep a system within a target state. This process is dependent upon the operator's knowledge of how the system functions as well as his or her experience working with the system. How well an operator is able to maintain control over the system is influenced by the behavior of the system as well as the operator's expectation of system behavior. When the system behavior corresponds with the operator's prediction, it is reasonable to anticipate that control can be maintained. During routine surgery, with no unanticipated events, it is expected that an experienced anesthesiologist should be able to maintain the appropriate level of sedation for the patient. However, if there is an adverse reaction to a drug or unexpected change in vital signs, the anesthesiologist can only maintain or regain control if they posses the appropriate knowledge or previous experience. When an operator, such as the anesthesiologist, is not able to successfully cope with changes in system behavior, it may not be due to a lack of training. Instead, it may be an artifact of the incompatibility of human cognitive ability and control of the type of system.

An important aspect to understanding how humans control systems is to account for how people interpret system behavior and how they arrive at their decisions to act. Many of the tools and resources for understanding human ability to control systems can be found in the domain of cognitive psychology. Cognitive psychology provides models on perception, learning, declarative and episodic memory, problem-solving strategies, mental representations, situational awareness, attention, and so on. Cognitive psychology also provides tools to improve the quality of management of the cognitive process, which aims at teaching strategies to maintain control of the system through an evaluation of risk and system integrity (Paries & Amalberti, 2000). Successful models for human control theory should be based on our understanding of these important, basic cognitive processes.

The Current Research

This paper presents the argument that natural and engineered systems differ in terms of their transparency, linearity, and adaptability. It also suggests that the cumulative effects of these characteristics in natural systems may lead to increased control error. A central goal of this research is to determine whether this is true. Previous studies in spatial navigation have explored the effects of system transparency on human ability to interact with the system (Cohen, 1996; Sebrechts, Lathan, Clawson, Miller, & Trepagnier, 2003; Wang, 2003; Witmer, Bailey, Knerr, & Parsons, 1996). These studies have shown that performance improves when people are provided with visual representations of an environment before navigating the actual environment. Through the use of maps, descriptions, and even virtual simulations, people are able to create mental representations of the environment. The system becomes transparent because the person is able to see the components and their interactions. Mental representations of a territory are important for good performance in a spatial navigation task just as mental representations of system operation are important for good performance in a control task. Just as with control tasks, optimal performance in spatial navigation necessitates manipulating the current system state (location of individual) to correspond with a given target state. Resultantly, it is reasonable to apply an understanding of system transparency from spatial navigation to control tasks. Due to the availability of information on the effect of transparency in human performance, the current study will use only simulations of nontransparent systems in the experimental task.

Though there are studies that have addressed some aspects of tracking complex dynamic process (Guastello, 2002; Heath, 2002; Ward & West, 1998), there remains a lack of research exploring human performance in controlling them. In a recent publication, Guastello (2006) states, "Studies on the nature of the ability to choose an effective control action or likelihood of human error while controlling a chaotic system have not been published yet" (p. 109). The current study addresses human control performance in chaotic-like systems that have nonrepeating, difficult-to-predict, adaptive, and nonlinear behavior. It attempts to expand our understanding of human performance in control settings that have not yet been fully explored.

Furthermore, target outputs within dynamic systems can vary depending on changes in demand on the system. A target heart rate for a person at rest differs from a target heart rate for the same person during exercise. Performance demands often change as a part of regular system operation. Such changes to the system target state require a controller to be able to adapt in order to preserve optimal performance. Successful control is dependent upon matching system inputs to system states in order to produce a desired output.

As mentioned previously, control can be conceptualized as manipulating the inputs of a system to maintain a desired target or output. At attractors, systems operate in a state of relative equilibrium. If a target output corresponds with an attractor, little effort is needed to maintain the target state. If the target output does not correspond with an attractor, additional energy or force in necessary to sustain that output. Energy can be introduced to the system in the form of inputs. Inputs to a system could include energy, money, and other resources. An automobile at rest on flat terrain is in a state of relative equilibrium. Energy in the form of fuel resources can be used to disrupt the equilibrium and move the automobile. Forces such as friction and gravity work on the automobile to push it back toward a stationary state where it is in equilibrium. Fuel resources must be continually put into the system to maintain an output speed other than stationary. Control is achieved by changing the inputs in an effort to reach the performance goal. Similarly, participants in this experiment will manipulate a joystick to control system inputs in an effort to maintain a specified target state.

Optimal system performance can be achieved when a controller is able to sustain system output in the target area while keeping costs at a minimum. Attempting to maintain this balance can drive a system to the limits of its operation. A boundary condition is a system state where production or output can move out of normal operating conditions. Crossing boundary conditions may lead to dramatic changes in output, operating costs, or even system failure. Because of these possible changes, pushing a system past its fundamental limits is typically undesirable. For this reason, many systems are designed to operate within a set of known system boundaries that maximize output while keeping risk low. Safeguards are built into these systems to prevent the operational state from moving beyond critical boundaries or to warn operators that a boundary is being approached. However, nonlinearity and system self-adaptation may lead to an increased risk of breaching boundary conditions and moving into an unfamiliar and possibly unpredictable state of operation. Because natural systems often display characteristics such as nontransparency, nonlinearity, and adaptability, it is suggested that the risk of inadvertently causing a system to rupture boundary conditions is greater in the context of controlling natural systems, than it is in the context of controlling engineered systems.

With nontransparent systems, operational parameters and boundary conditions are typically discovered through a process of repeated trials and experience. Based on data from such trials, models are created to represent the general behavior of the system. These models are used to aid system controllers in predicting the effects that inputs will have on the system. For the most part, these models work well; pilots fly airplanes, meteorologists advise of dangerous weather, anesthesiologists keep patients alive. However, there are times when systems behave in ways that differ from the predicted models. At these times, error increases and effective control can be lost. The risk for loss of control is greater in nontransparent systems where the system behavior is hidden from the controller. Participants in the current research will not have the benefit of visual cues to aid them during the experimental trials. Instead, they will need to rely on exploration to develop a mental representation of the system.

Adaptable systems are vulnerable to change. Their operational parameters can be influenced by changes in the environment, by changes to component relationships, or even by system inputs. Because of this vulnerability, control parameters within adaptable systems can change without any indication. For a system that is functioning near operational limits, the effects of change on boundary conditions can be disastrous, especially from a control perspective. Unanticipated change in system behavior can lead to a drastic increase in control error. Successful control of the experimental task used in this study will require that the participant compensate for changes in system behavior.

Within the experimental task in the current study, the characteristics of linearity and adaptability are manipulated with nontransparency held constant. The participants are not given any visual aids referring to attractor location, size, or strength, and will have to determine attractor characteristics by experience alone. Linearity in the system is adjusted by the abruptness of change in attractor forces. Linear conditions have attractors with smooth, continuous force strengths while attractor forces in nonlinear conditions may change in abrupt, nonadditive degrees. Finally, adaptability is represented by a susceptibility to change. During adaptive conditions, the target area will periodically move from one basin within the system to another. This change will require the participant to adjust their controls to correspond to system behavior in the new attractor basin. Nonadaptive conditions will have target locations that periodically move but remain within the same attractor basin.

The current research focuses on differences in how well people are able to control systems that have characteristics of either natural or technical systems. To accomplish these goals, this experiment utilizes a simulated control task in which the characteristics of adaptability and linearity can be manipulated. Participants act as operators in the simulated system. The system simulates a series of connected attractor basins. At every point along the operational space, there are forces that drive the system state toward an attractor. These forces vary depending upon initial conditions and the parameters that define the operation of the system. The current state of the system is represented by a cursor whose movement is controlled by the participant through the use of a joystick. Joystick manipulations represent inputs to the system. The location of the cursor at any given time represents the system output. The system output is dependent upon the relationship between the input and the system state at any given time. Participants use the joystick to keep the cursor within a specified target region in the system.

Primary Task

One main goal of this research is to determine if there is an effect on control performance for nontransparent systems that differ in terms of their linearity and adaptability, and if there is an interaction on control performance for certain characteristic combinations. Four experimental conditions are used to test these effects. Control performance is measured using root mean square error (RMSE), expressed in pixels, and percent time on target (PTOT).

Hypothesis 1. Condition one is linear and adaptive. Participants will have to deal with changes to the target region during adaptive transitions by adjusting control. This could lead to an increase in control error. However, they will not have to cope with nonlinearity in the system. As a result, it is expected that mean performance in this condition will be good with lower RMSE and higher PTOT scores.

Hypothesis 2. Condition two is nonlinear and adaptive. It is predicted that the lowest levels of performance will be seen in this condition. Initial performance will suffer while the participants first learn to interact with the nonlinear attractor forces. Additionally, when the target location changes to a new basin it will likely lead to increased control error while the participant adjusts for the change and becomes familiar with the new basin. Nonlinear attractor forces will likely make it more difficult to regain control after a change has taken place. It is predicted that mean performance will be poor with high RMSE and low PTOT scores.

Hypothesis 3. Condition three is linear and nonadaptive. Participants will not have to cope with changes to attractor basins or nonadditive forces. As a result, it is predicted that participants will produce the least amount of error in this condition resulting in the lowest RMSE scores and highest PTOT performance levels.

Hypothesis 4. Finally, Condition four is nonlinear and nonadaptive. It is predicted that there will be a performance deficit while the participant copes with the nonlinearity of attractor forces. However, because the participant only has to compensate for nonlinearity, once the participant has become familiar with the system it is expected that RMSE and PTOT performance will not differ significantly from Condition one.

Overall, I hypothesize that control performance will be highest for Condition three, in which participants do not have to compensate for either adaptability or nonlinearity. I predict performance to be similar in Conditions one and four, where participants will have to cope with either adaptability or nonlinearity. Finally, I predict that performance in Condition two will be significantly worse than in the other three conditions because participants will have to deal with adaptive and nonlinear forces.

Secondary Task

To help gauge the cognitive demand of each of the experimental conditions, a secondary stimulus-response task is included. As participants perform the tracking task, the target will occasionally flash green or red. Participants are instructed to respond to a green flash by pressing the trigger button on the joystick and not to respond to a red flash. Signal detection theory will be used to determine if the probability of missing a signal or giving a false alarm differs between the three conditions. The more cognitively demanding conditions should result in an increase in reaction times, fewer hits, and more false alarms due to interference with cognitive resources used for target tracking and prediction.

Hypothesis 5. Previous studies have demonstrated that when a secondary task is performed simultaneously with a tracking task, there is performance degradation on one or both tasks (Allen et al., 2004; Strayer & Johnston, 2001; Watson & Jones, 1998). I hypothesize that Condition two will be more cognitively demanding because participants will have to cope with the added complexity of nonlinear and adaptive system behavior. As a result I expect there to be a decrease in secondary task performance. Because participants will not have to cope with the combination of adaptability and nonlinearity in Conditions one, three, and four, I predict that they will show similar cognitive demands and that there will be no reliable difference between them in terms of secondary task performance.

In summary, while manipulating the characteristics of linearity and adaptability in a nontransparent system, I expect control performance to deteriorate when an operator is working with a system that is either nonlinear or adaptable. Participants may be able to successfully compensate control performance for systems in which only one of these characteristics is present. However, I hypothesize that they will not be able to continually compensate control in systems that are nontransparent, nonlinear, and adaptive.

METHOD

Participants

Fifty-three college students (28 male, 25 female) participated in this project as a way of fulfilling a requirement in an undergraduate psychology course. They ranged in age from 18 to 35, with a mean age of 21.3 (SD=3.54). All participants demonstrated normal or corrected-to-normal vision and received a perfect score on the Ishihara color blindness test (Ishihara, 1993). Forty-six participants were right-handed and 7 were left-handed. No participant reported any history of skeletal muscular disorder. All participants completed each of the four experimental conditions. To account for practice and fatigue effects, the order in which the conditions were presented was counterbalanced. To measure prior perceptual motor experience, which is used as a covariate, participants were asked to report how often they have used a joystick to play video games (Joseph & Willingham, 2000). Responses included 1 (never), 2 (a few times), 3 (more than a few but not very frequently), 4 (frequently), and 5 (regularly). The most common response was 2 (M=2.54, SD=1.03).

Apparatus

The participants performed a simulated manual two-dimensional control task with a pursuit display in which they used a Logitech attack III joystick to keep a crosshair cursor as close as possible to a target location on a 17 inch Dell E773c monitor with the resolution set at 1280 by 1024. The control task program displayed a white crosshair cursor 15 pixels in diameter and a smaller solid white target circle 13 pixels in diameter against a black background. The joystick functioned as a velocity controller and the cursor moved in the same direction as the joystick. The movement of the cursor was also influenced by single point attractor basins that were mapped out on the screen but were not visible to the participant. The attractor basins varied in position, arc angle, direction, and strength. The program was set such that it was possible for the cursor to overcome any attractor. The maximum velocity at which an attractor could pull the cursor was set at 512 pixels per second. The joystick could cause the cursor to move at a rate between 0 and 680 pixels per second, depending on how far it was moved in any direction. None of the basins extended off of the monitor display.

Four different basin arrangements were developed. All four of the experimental conditions were set up for each of the four basin arrangements, creating a total of 16 possible maps. The trials were counterbalanced with one map from each of the basin arrangements. The position of the crosshair and the target were sampled every 33 ms by a computer running on a Pentium 4 CPU with 256 MB of RAM. The cursor was scored as on target if the crosshair overlapped the target circle when the positions were sampled.

At random intervals between 5 and 30 seconds, the target flashed either green or red for a duration of 200 ms. Participants were instructed to respond to green flashes as quickly as possible by pressing the trigger button on the joystick with their index finger. They were instructed not to respond to red flashes. Green and red flashes were equally probable and their order of presentation was unpredictable. The computer recorded whether participant response with the trigger button was a hit, miss, false alarm, or correct reject. Reaction time was recorded as the elapsed time from signal onset to trigger response.

Procedure

Participants were introduced to the control task and asked to manipulate the joystick with their preferred hand. They were asked to move the joystick so as to keep the crosshairs as close as possible to the target throughout the duration of the experiment. At the beginning of each trial the target circle flashed and a countdown was set for 3 seconds as a warning signal that the trial was about to begin. Participants then performed a 10-minute practice trial to become familiar with the task. Following the practice trial, participants performed the four experimental trials which lasted 10 minutes each. Between trials, participants saw a screen prompting them that the trial was complete and were allowed a brief rest break. At the conclusion of the four experimental tasks, participants were asked to fill out an open ended question asking them what strategies, if any, they used to keep the cursor in the target region. Participants received a credit slip for their class and were thanked for their participation.

RESULTS

Data from 5 participants were excluded from the analyses; 4 participants had variable scores outside of an acceptable range and 1 participant did not complete all four experimental conditions. Figure 1 shows the RMSE for each of the four conditions. As can be seen in the graph, RMSE scores were highest in Condition two. A within group analysis of variance (ANOVA) was used to analyze differences in performance as measured by RMSE. The analysis indicated a significant difference in RMSE scores, ($F(3, 47) = 25.81$, $p < .001$).

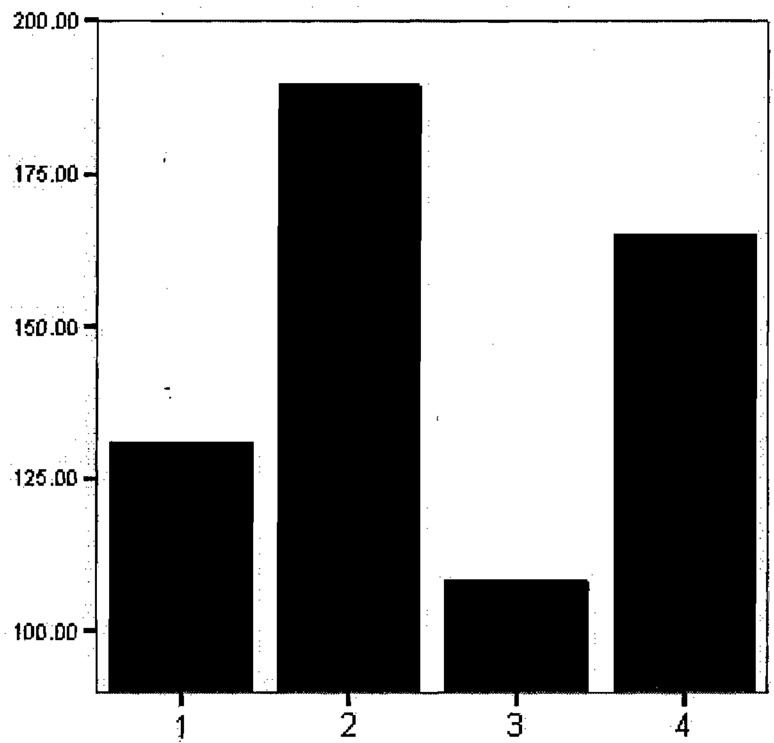

Figure 1. RMSE Control Error by Condition

To help determine if there are differences in human ability to control engineered versus natural systems, we compared performance in Condition three (nonadaptive, linear) ($\underline{M}$=108.18, $\underline{SD}$=48.46) to Condition two (adaptive, nonlinear) ($\underline{M}$=189.50, $\underline{SD}$=42.14). Pairwise comparisons showed a significant mean difference between the conditions ($\underline{MD}$=81.313, $\underline{p} < .001$). We were also interested in whether participants would be able to compensate control performance when exposed to only one of the independent variables. Pairwise comparisons showed no significant difference in RMSE scores ($\underline{MD}$=22.82, $\underline{p}$=.058) between Condition one (adaptive, linear) ($\underline{M}$=131.0, $\underline{SD}$=59.59) and Condition three (nonadaptive, linear) ($\underline{M}$=108.18, $\underline{SD}$=48.46), suggesting that adaptability did not influence performance within linear systems. There was, however, a significant difference in mean difference scores ($\underline{MD}$=24.22, $\underline{p}$=.006) between Condition two (adaptive, nonlinear) ($\underline{M}$=189.50, $\underline{SD}$=42.14) and four (nonadaptive, nonlinear) ($\underline{M}$=165.27, $\underline{SD}$=42.23), suggesting that participants were not able to compensate control with the presence of both independent variables.

The PTOT results for each condition can be found in Figure 2. A within group ANOVA reveled a significant difference between mean PTOT scores, ($\underline{F}(3, 47) = 45.361$, $\underline{p} < .001$). Participants were able to keep the cursor over the target 25% more often during the nonadaptive, linear condition ($\underline{M}$=29.63, $\underline{SD}$=20.2) as compared to the adaptive, nonlinear condition ($\underline{M}$=2.7, $\underline{SD}$=3.37), indicating that adaptability and nonlinearity together drastically degrade control performance. Less drastic but significant performance degradations were also found when looking at the variables of adaptability and nonlinearity individually.

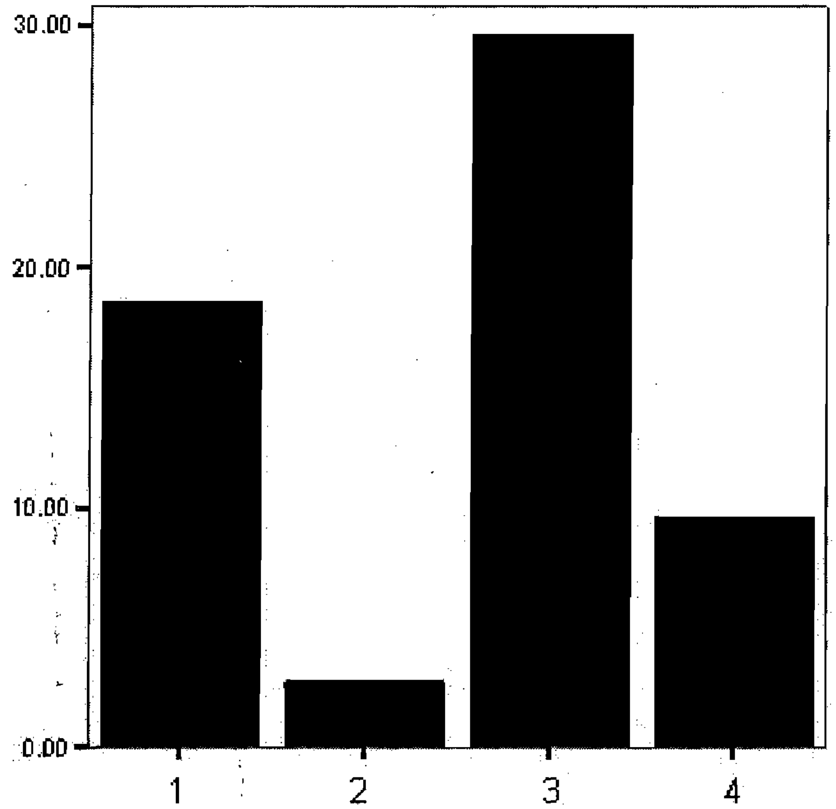

Figure 2. Percent Time on Target by Condition

The reaction time to the secondary stimulus response task is presented in Figure 3. A within group ANOVA indicated that participants responded significantly slower during the adaptive, nonlinear condition, suggesting that controlling such systems is more cognitively demanding, ($F(3, 47) = 5.58$, $p = .01$). No reliable difference was found in reaction time between the other three conditions. Contrary to the hypothesis, no significant difference was found in miss rates between the four conditions. However, a significant difference was found for false alarms ($F(3, 47) = 2.74$, $p < .05$). The probability of making a false response when the target flashed red was 58% higher in the adaptive, nonlinear condition when compared to the adaptive linear condition.

As can be seen in Figure 4, results from a d′ analysis showed that the signal in the secondary task was readily detected by the participants in all four conditions. A within

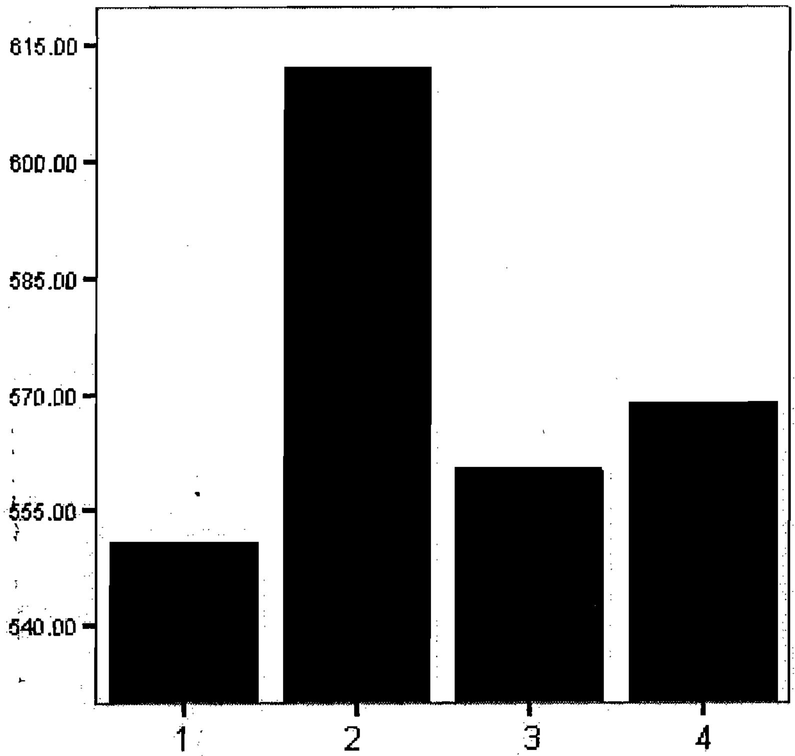

Figure 3. Reaction Time by Condition.

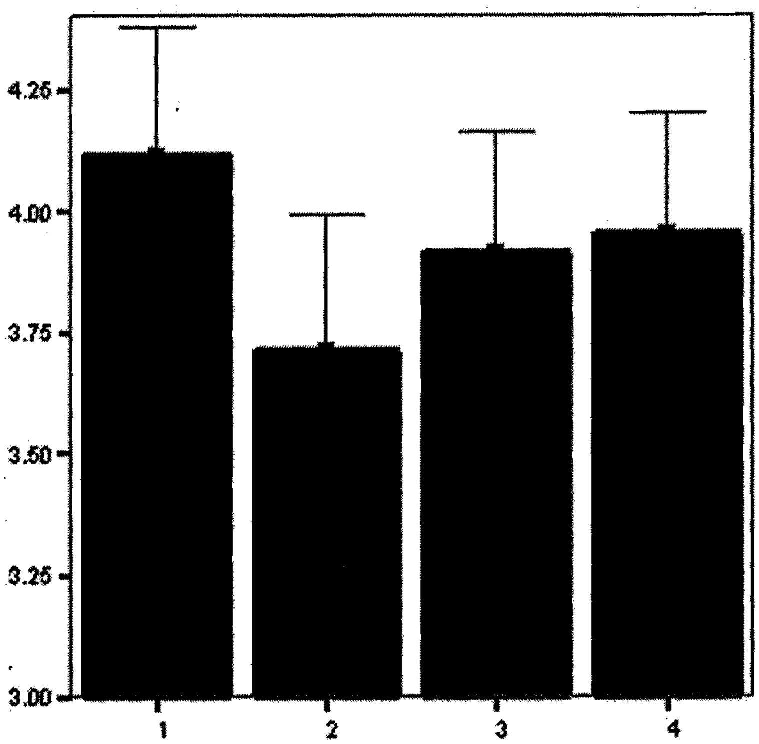

Figure 4. D′ by Condition

group ANOVA showed a significant difference in the sensitivity index ($F(3,47) = 4.207$, $p < 0.01$). Pairwise comparisons showed that signal detectibility was significantly lower in Condition two ($M = 4.118$, $SD = 0.901$), as compared to Condition one ($M = 3.713$, SD 0.961=) which suggests a greater cognitive demand on the participant during the adaptive nonlinear condition. No other significant differences in d' scores were found.

Figure 5 displays the decision criterion (λ) for each condition. Analysis showed a significant difference between them ($F(3, 47) = 4.06$, $p < .01$). Pairwise comparisons reveled that participants were less conservative in their judgments during the adaptive, nonlinear condition ($M = 1.995$, $SD = 0.421$) as compared to the adaptive linear ($M = 2.23$, $SD = 0.435$) and nonadaptive, nonlinear ($M = 2.186$, $SD = 0.457$) conditions.

This finding is consistent with the other measures of participant performance which show that performance was impeded by the presence of the adaptive and nonlinear system characteristics. However, no significant difference was found in the λ scores when comparing the adaptive nonlinear condition to the nonadaptive, linear condition ($M = 2.075$, $SD = 0.394$). This finding is not consistent with the results of other measures of participant performance. As performance in the secondary task was good in all four conditions, it is possible that there was a ceiling effect and that these differences are due to random error.

Joystick experience was used as a covariate to determine whether previous perceptual motor experience resulted in better performance. An analysis of covariance (ANCOVA) indicated no significant main effect for joystick experience for RMSE scores ($F(3, 47)=2.03$ $p=.115$), for PTOT scores ($F(3,47)=1.59$, $p=.21$), or for the secondary task RT scores ($F(3, 47)=2.56$, $p=.058$). More joystick experience did not

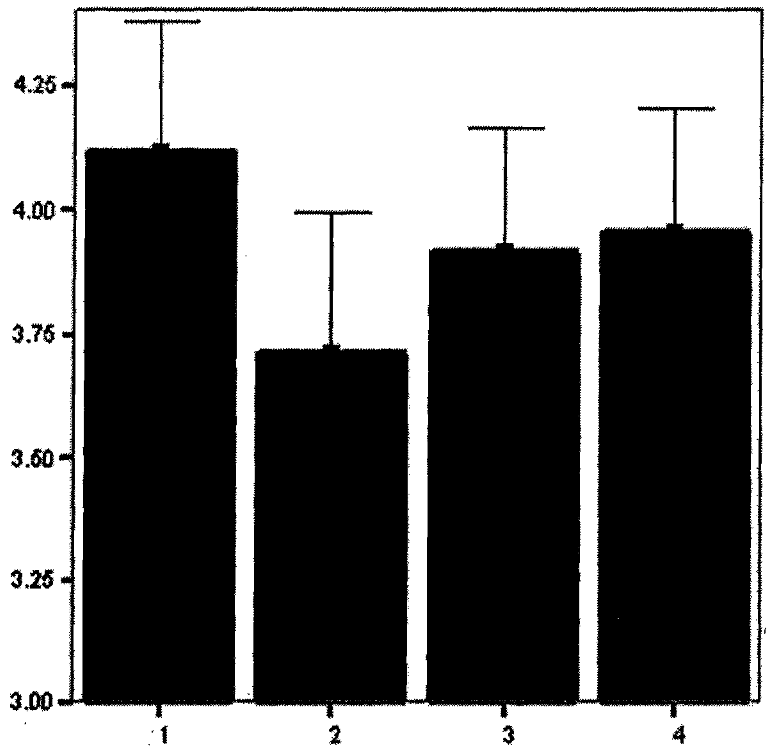

Figure 5. Criterion by Condition

influence any of the control performance measures.

After participants had completed the experimental task, they were asked to answer a brief open-ended question asking them to describe any strategies that they utilized to accomplish the task goals. All 48 participants responded to the question; some participants described multiple strategies yielding a total of 53 responses. These 53 responses were grouped into three general strategies. Twenty-five participants described a strategy that involved discovering how the invisible forces affected the cursor. Methods for accomplishing this included some of the following: moving toward the target area from multiple directions to find the easiest approach, letting the cursor drift in its natural flow, and avoiding areas that pulled the cursor away from the target. Eight participants reported that they tried to move the cursor slowly to stay close to the target for a longer period of time. Seven reported that they just tried to get close to the target and hold still. Thirteen participants described strategies for the secondary task. They all indicated that they tried to focus on the target dot at all times so that they would not miss a signal.

DISCUSSION

The results of this study suggest that the characteristics of adaptability and nonlinearity influence human ability to track and control systems. In support of the hypotheses, participants showed the poorest RMSE performance during Condition two (adaptive, nonlinear). This finding suggests that systems with the characteristics of adaptability and nonlinearity, such as natural systems, are more difficult for human operators to control. Performance in Condition four (nonadaptive, nonlinear) was significantly better than in Condition two but not as good as Conditions one (adaptive, linear) and three (nonadaptive, linear). Conditions one and three did not differ significantly from one another in RMSE, suggesting that participants were able to compensate for adaptive behavior when the system attractor forces were additive. The differences between performance in Conditions two and four suggest that participants were not able to compensate for adaptive behavior when nonlinearity existed.

The analysis of PTOT also lends support to the conclusion that adaptive, nonlinear systems are more difficult to control than nonadaptive, linear systems. The results show that control performance was ten times better when the system did not display adaptability and nonlinearity. Participants are far more successful at keeping the cursor within the goal space when the system does not display characteristics common to natural systems. This finding is important because it suggests that operators are less capable at maintaining a target control range when working with adaptive, nonlinear systems.

The results of the secondary task suggest that a combination of adaptability and nonlinearity is more cognitively demanding for the operator. Participants are 58% more likely to give a false signal response when controlling a system that is both adaptive and nonlinear. Likewise, reaction times are about 10% slower during the adaptive, nonlinear condition when compared to the other three conditions. Reaction times for the other conditions are not significantly different from one another. These findings are important because the slower reaction times for the adaptive, nonlinear condition suggest that controlling this type of system places a higher cognitive demand on the operators. This puts an increased strain on the operator. It is no surprise then that the condition with the poorest control performance also had the slowest reaction times on the secondary task. This finding is consistent with studies reporting performance degradation for tasks that have a high cognitive demand (Allen et al., 2004; Strayer & Johnston, 2001; Watson & Jones, 1998). The secondary task strategy described by 13 participants in the open ended survey question suggests that the simulated activity was cognitively demanding enough to require participants to use a compensatory strategy. When individuals are required to perform multiple tasks simultaneously, they often utilize balancing techniques to reduce the amount of attention resources that are dedicated to one task so that they have more resources available to complete the other task.

Like previous research in the area of controlling complex, dynamic systems, the current study provides evidence that people have difficulty compensating for adaptive change in system output, especially when the changes are nonlinear (Brehmer, 1992; Brehmer & Dorner, 1993; Kantowitz, 2001). It has been suggested that this is the result when people are unable to understand or predict how the whole system will respond to all control movements (Dorner, 1996). Recent research has shown that providing operators who are controlling a natural system (i.e., anesthesiologist controlling vital signs of human patient) with real time visual feedback on the effects of their manipulations leads to better control performance (Drews, Syroid, Agutter, Strayer, & Westenskow, 2006). Providing a visualization of current system behavior, interconnectivity of system components, and possible future system states could help operators improve control performance by aiding in the prediction of future system states and by increasing system transparency. It is likely that such visualization aids would also lead to improved control performance in other natural system domains where operators often have to cope with adaptability and nonlinearity.

The finding that previous joystick experience is not a good predictor of manual control performance is not consistent with research by Joseph and Willingham (2000). In their study, participants with higher perceptual motor experience performed better on a manual pursuit tracking task than those with less experience, however, the effect disappeared as participants became more familiar with the task. The influence of previous joystick experience is important to note because it provides evidence that differences in control performance are the result of the manipulations to the independent variables and not an artifact of prior joystick use.

In this paper, it is argued that both natural and engineered systems are deterministic, which suggests that the output targets have a degree of spatial predictability. The study by Joseph and Willingham (2000) found that tracking performance was better when following a predictable pattern than it was when following a random output. They also discovered that practice did not eliminate this advantage, suggesting that performance improves only while working with nonrandom output. As a result, it is likely that manual tracking research that utilizes pseudo random outputs will not fully capture potential differences in human performance when controlling real world systems that have degrees of predictability. In an attempt to make the results of the current research more applicable to real world control tasks, the experimental task for the current study was designed to have spatial predictability.

Although real world systems do tend to have deterministic output, people are not always successful at predicting their outputs. In this study, we suggest that this is due, in part, to system characteristics such as transparency, adaptability, and linearity. It is likely that performance differences between the four experimental conditions are the result of variations in output predictability caused by adaptive behavior and nonlinear attractor forces. Thus, real world systems (i.e., anesthesiology, family therapy, governments, etc.) that display such characteristics are also likely to be more difficult for human operators to control.

The current study presents the argument that adaptability and nonlinearity are important characteristics of natural systems that influence human ability to exert control over a system. One goal of the experiment presented in this study was to present a unique approach to empirically address the effects of adaptability and nonlinearity on control performance. To accomplish this goal, the concepts of adaptability and nonlinearity were operationally implemented into the simulated control task. As it is unlikely that characteristics such as adaptability and nonlinearity could be fully encapsulated by any one experiment, the current study incorporated limited operational definitions of these system attributes.

A general construal of adaptability is an interaction between a system and the environment that preserves system integrity and which results in some type of system modification (Collier & Hooker, 1999). In the current experiment, adaptability was represented as a change in system behavior depicted as how the system interacts with the cursor in relation to the target; thus the system structure remained intact while the relationship between its inputs and outputs changed. This was accomplished by changing the location of the target from one attractor basin into another basin. The result was a change in how the system responded to the operator's manipulations without altering system integrity. Adaptability in real world systems can occur without indication as vulnerable operational parameters are shaped by changes in the environment. It may be noted that adaptability in the experimental simulation was not the result of changes in the environment or as a vulnerable response from the operator's inputs. It would have been possible to simulate adaptability in other ways. One possibility was to initiate a change in the target location as a response to user control inputs which would mimic a vulnerable response to inputs from the environment. This representation of adaptability was not incorporated into the simulation used in this experiment because the aspect of adaptability that was of interest was the operator's ability to keep control error at a minimum while dealing with the behavior change that is the result of the adaptation rather than the cause of the adaptation. A second method of simulating adaptive behavior that was considered for the simulation was to dynamically change the attractor basin parameters (i.e., shape, force, etc.) without the target location changing its physical location. This form of adaptation was not implemented because it would have presented the participant with a changed basin arrangement in the adaptive conditions that was not consistent with the basin arrangements in the nonadaptive conditions. Instead, adaptability as it was implemented into the simulation used in the current experiment presented participants with basin arrangements that remained constant but allowed for differences in how the cursor behaved around the target location.

As with adaptability, various definitions of nonlinearity exist. Linear systems have a predictable response to stimuli. In a linear system it is possible to apply an understanding of a system's response from one input to the prediction of the system's response to a second input. In other words, what we know about how a system behaves in response to user control at one point provides information on how the system will behave in response to user control at another point. Within a linear system, a change to an input results in a proportional change to the output. On the other hand, within nonlinear relationships, small inputs can lead to substantial, nonadditive changes to the system output (Guastello, 2006; Prigogine & Stengers, 1984). Nonlinearity in the current study was simulated in this way. Within the linear attractor forces, changes to the input controls resulted in proportional deviations in the location of the cursor. However, within the nonlinear attractor forces, small changes in the controls could result in nonproportional changes in cursor position. Although the current application cannot give a full portrayal of nonlinearity, it likely captures a part of performance degradation that is the result of people responding to outputs that are the product of nonadditive inputs in a control setting. Future experiments exploring control performance involving nonlinearity as an independent variable would likely benefit from the addition of different types of attractors such as limit cycle attractors, quasiperiodic attractors, and chaotic attractors. Incorporating these additional types of attractors would allow the creation of system models that display diverse qualitative changes in behavior that result from small changes in input (Jagacinski & Flach, 2003) which would also encompass a broader definition of nonlinearity.

Limitations

One limitation to this research is the fact that we used an engineered simulation to mimic characteristics of natural systems. This was done because it was not feasible to find a real world natural system that differs from an engineered system only in terms of linearity and adaptability. Furthermore, it is unlikely that the control interface between the two systems would have been compatible. It may have been possible to develop an engineered system that differed from a natural system only in terms of linearity and adaptability; however, the results of such a study may have been applicable only to that specific application. Furthermore, research has shown that simulation, even low fidelity simulation, can be effective and can provide good transfer (Jenstsch & Bowers, 1998; Koonce & Bramble, 1998; Patrick, 1992; Salas, Bowers, & Rhodenizer, 1998). In developing a general control simulation in which the characteristics of linearity and adaptability were manageable, we hope to be able to generalize the findings to a broad theory and a wide range of applications.

An additional limitation to this study is the inability to control for all the potential differences in characteristics between natural and engineered systems. This paper identifies three characteristics that differ between natural and engineered systems: transparency, adaptability, and linearity. However, the experimental task addresses only adaptability and linearity. The decision to make all of the conditions nontransparent was made to reduce the complexity of the experimental design and because many real world control tasks do not provide operators with displays that provide system transparency. Instead, transparency often develops through expertise and mental models. The task in this study was nontransparent but it likely became more transparent as the participant continued to interact with it. This is important to address because, in the nonadaptive conditions, the target region stayed within the same attractor basin. Participants thus had the opportunity to develop a more complete mental model of that region of the system, making that region more transparent. In contrast, when controlling the adaptive system, participants had a greater opportunity to develop a mental model of the entire system.

The responses to the open question about the primary task suggest that participants actively explored the system in an effort to understand its behavior. Several participants mentioned that they tried to avoid the invisible barriers or troublesome spots that would cause the cursor to move away from the target. A couple participants even reported that sometimes going in the opposite direction from the target and circling the cursor around the screen to approach the target from the other side was the fastest way to return to the target region. These responses lend support to the idea that operators develop mental models to increase system transparency. They also indicate that during a control task, operators actively seek out or develop mental representations to aid them in reaching the task goal. Utilizing such models and strategies could potentially improve control performance as long as the system does not change its behavior. Although transparency was not actively manipulated in the conditions, it is likely that it did vary between the four experimental conditions due to learning. Future studies could be conducted in which transparency is actively manipulated to determine what influence it would have on control performance.

Finally, the lack of system specificity may have influenced participants' performance. On a posttask evaluation, many participants reported feeling a lack of interest in the task which resulted in a sense of boredom. As a result, the engagement of the task was likely prejudiced. Engagement refers to the participant's motivation to take the task seriously (Gray, 2002). Even though not all real world tasks are particularly engaging, it is possible that control performance within the simulation used for the current research was influenced by the lack of engagement that the task displayed. Integrating a more specific and interactive goal into future experimental tasks would likely improve participant interest in the task and subsequent task performance.

Unique Contributions

Although the results of this research support previous decision making research conducted on complex, dynamic systems, this study is unique in its approach to the problem. Many previous studies address control and decision making issues from a scaled world simulation domain (Ehret, Gray, & Kirschenbaum, 2000; Gray, 2002). A scaled world is an artificial environment that mimics component relationships that are found in complex environments. Often these simulations are controlled by a process of entering keystrokes as a means of controlling inputs to the system. In addition, the current study borrows techniques from manual tracking research, which is also used to explore manual, perceptual, and cognitive limitations of human control. The simulated control task in the current study combines techniques from both areas to address the issue of human control. This is useful because it provides an opportunity wherein the experimental strengths of both domains can be used together, which should lead to results that are more representative of actual control performance.

Another important contribution of this study is that it employs an experimental approach to address control differences between natural and engineered systems. Prior papers have explored theoretical differences between natural and engineered systems (see Collier & Hooker, 1999) and some have even examined ways in which control performance can be improved in natural systems (i.e., Drews et al., 2006), but few, if any, studies have been conducted that directly compare control performance between natural and engineered systems. The current study is a preliminary step into experimentally studying differences in control performance when comparing natural and engineered systems. It is typical for fields that deal in the control of natural systems to borrow straight from engineering control theory. Because fundamental differences exist between natural and engineered systems, there are likely fundamental differences in human ability to control them. It may not be appropriate to apply all aspects of an engineering control theory into a domain that deals in the control of natural systems. The current research provides evidence that attempts to improve control in the domain of natural systems could greatly benefit from a separate and tailored theoretical framework of control.

This research introduces a novel approach to exploring differences of system characteristics on control performance. The experimental task for this study is a low fidelity simulation developed using basic concepts from dynamic systems theory. The simulation incorporates aspects of dynamic systems theory into a control task setting. Concepts such as attractors, repellers, bifurcation, and boundary conditions are used to create and manipulate different types of system characteristics. Previous manual tracking research has used a dynamic systems approach for analysis of performance on a sinusoidal tracking task (Liao & Jagacinski, 2000). However, few studies, if any, have used dynamic systems theory concepts as the basis for the control task. Using a dynamic systems theory approach is advantageous to studying system control because dynamic systems theory techniques do a good job at modeling behaviors of both natural and engineered systems (Butner, 2007). It is likely that using dynamic systems theory for modeling control of system behavior will also provide important insights into understanding limits of human control ability as well as help develop techniques to aid human control.

Further development of the simulation could prove useful in studying and modeling many different paradigms . Building the simulation with additional concepts from dynamic systems theory (i.e., multiple types of attractors, escapement forces, etc.) would allow future studies to experimentally explore how other system characteristics, such as hysteresis and bifurcation, influence human control performance. Additionally, specific models could be build to represent behavior of specific systems. Models could include domains from ecological impact of agriculture to decision making, from traffic flow regulation to health care, and from marriage relationships to global warming.

Conclusion

The results of this study indicate that systems that display characteristics common to natural systems are more difficult to control than those that display characteristics common to engineered systems. Specifically addressed were the variables of adaptability and linearity. As presented in this paper, due to their vulnerability to changes in the ecology and potential for evolution, natural systems tend to be adaptive and nonlinear, but engineered systems do not have the ability to adapt to change and are designed to have linear behavior. This study provides evidence that natural and engineered systems differ in terms of the demands that they place on human operators. As fundamental characteristics differ between natural systems and engineered systems, and as there are drastic performance differences in human ability to control systems that differ in these fundamental characteristics, it is logical to conclude that efforts should be made to establish distinct theories of control for natural and engineered systems. Additionally, visualization and control interfaces should be designed to aid human operators cope with problematic system characteristics such as nontransparency, adaptability, and nonlinearity. With continued work in these areas it is hopeful that progressive advances will lead to improvements in the quality of our connections with natural systems and result in less error when controlling such things as social relationships, environmental interactions, and human life.

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